

Original Article

An Intelligent Hybrid Model for Predicting Building Thermal Load from Geometric and Envelope Attributes

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Abstract - Prediction of building thermal loads is vital for improving energy-efficient building design, sustainable infrastructure planning, and intelligent energy management in modern civil engineering applications. Existing thermal load prediction models often struggle to attain nonlinear dependencies and feature interactions in structured building datasets. Several existing studies also focus primarily on component-level thermal analysis or restricted climatic conditions, reducing broader prediction generalization and interpretability. To overcome these limitations, this model introduces a hybrid TabNet-ResMLP approach combined with interaction-based analysis to provide interpretable insights into the influence of geometric and envelope parameters on building thermal load. TabNet was employed for attentive feature selection and contextual feature weighting, while ResMLP performed residual nonlinear regression for modelling complex thermal behavior. The proposed model was validated using the Energy Efficiency dataset. Experimental evaluation achieved Root Mean Square Error (RMSE) values of 1.65 and 1.95, Mean Absolute Error (MAE) values of 1.12 and 1.38, Mean Absolute Percentage Error (MAPE) values of 6.0% and 7.1%, and Coefficient of Determination (R^2) values of 0.98 and 0.97 for Heating Load (HL) and Cooling Load (CL), respectively. Feature importance, sensitivity, and interaction analyses further identified relative compactness, Surface Area (SA) and Overall Height (OH) as dominant parameters influencing thermal demand variation. The findings establish the efficacy of the proposed framework for early-stage building energy assessment, sustainable architectural design, and energy-efficient building operation.

Keywords - Building energy, Cooling Load, Deep Learning, TabNet, Sensitivity analysis, Heating Load.

1. Introduction

Thermal load in a building refers to the amount of heating or cooling energy that is needed in order to keep the indoor environment comfortable. Thermal load will depend on the geometric characteristics and envelope design of a building. Geometric characteristics such as the shape of the building, its height, OA, SA, and RC define how solar radiation affects the building. The characteristics of the envelope, like walls, roof, and glazing components, determine heat gain and loss by means of thermal resistance, solar radiation, and ventilation between the interior and exterior surroundings. The optimum design of geometry and envelope will decrease unnecessary heat gain [2].

The significance of minimizing thermal loading of the building becomes greater because of the high energy consumption of the buildings industry. Buildings consume a huge proportion of the overall energy usage and carbon emissions, which are mainly attributed to Heating, Ventilation, and Air Conditioning (HVAC) needs [3]. Rapid urbanization, population growth, and expanding infrastructure in developing countries have intensified construction

activities, while existing buildings in developed regions continue to consume considerable operational energy. In hot climates, cooling demand has risen sharply due to increasing ambient temperatures and widespread adoption of air-conditioning systems [4]. Heating demand remains substantial in colder climates, contributing significantly to seasonal energy consumption. These challenges, together with the impacts of climate change, have emphasized the need for energy-efficient building design strategies that reduce thermal loads and support sustainability goals.

Several methods employed for the purpose of determining the impact of design constraints of buildings on their thermal performance. Physical modelling methods such as Energy Plus (EP), Transient System Simulation Tool (TRNSYS), and Design Builder (DB) are commonly used to model heating and cooling load profiles [5]. These tools provide detailed and reliable results, yet they require extensive modelling effort, calibration, and computational resources. Statistical techniques, including regression models, offer simpler analytical frameworks, yet they are limited in capturing nonlinear relationships among multiple design



variables. Recently, ML algorithms like Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RF), and Gradient Boosting (GB) have shown enhanced predictive performance. However, they require exhaustive parameter tuning and lack interpretability or failed to sufficiently capture the relationship between attributes within tabular data [6].

Recent improvements in Artificial Intelligence (AI) and ML have improved the prediction of building thermal loads using geometric and envelope parameters. Although various models have demonstrated high predictive accuracy, most existing studies focus primarily on performance rather than interpretability and interaction-based analysis of input features [7, 8]. In particular, the combined influence of multiple design attributes on thermal load variation remains insufficiently explored, and many conventional models lack the ability to simultaneously perform adaptive feature selection and capture feature-level dependencies in structured datasets. Thus, there is a need to create an interpretable deep learning framework that can be used to perform adaptive feature selection, nonlinear interaction learning and simultaneously predict the heating and cooling load with accurate performance on structured building energy datasets. In this regard, the current study investigates a novel hybrid TabNet-ResMLP model to simultaneously predict heating and cooling loads based on structured building energy data. The novelty of the proposed work is that it combines TabNet's attention-based feature selection with the nonlinear regression ability of Residual Multilayer Perceptron (ResMLP), which provides both high prediction accuracy and better interpretability. In contrast to other studies focusing mainly on predictive performance, the proposed framework additionally includes feature importance analysis, sensitivity analysis and feature interaction analysis to give insights into the contribution of geometric and envelope characteristics to the thermal behaviour of buildings. The proposed framework is unique in using attention-guided feature learning together with the residual nonlinear modelling and comprehensive interpretability, which are not explored in the current methods for thermal load prediction. The major objects of this research are given below:

- To develop a hybrid TabNet-ResMLP framework for simultaneous prediction of HL and CL.
- To integrate attentive feature selection with residual nonlinear regression for improved feature representation and thermal load prediction.
- To analyse the influence of geometric and envelope parameters using feature importance, sensitivity analysis, and interaction analysis.

The remainder of this paper is structured as follows: a review of the related work presented in Section 2, the methodology and proposed method are explained in Section 3, Results and analysis are presented in Section 4, and finally, the study is concluded with future instructions in Section 5.

2. Related Works

Zhang et al. [9] presented a Grey Wolf Optimizer-Convolutional Neural Network-Long Short-Term Memory (GWO-CNN-LSTM) framework for predicting building cooling load using simulation data generated through SketchUp, EnergyPlus, and OpenStudio. The GWO was utilized for hyperparameter tuning of the CNN-LSTM framework to improve forecasting performance. The proposed model attained a 0.9266 R^2 value with 327.4012 W of RMSE. However, the study relied on simulation-based data from a single office building and excluded real-time operational building conditions and multi-climate validation.

De Paula et al. [10] developed a Building Information Modelling (BIM)-based ML approach for predicting Energy Use Intensity (EUI) and Operational Energy (OE) of office buildings during the conceptual design stage using 210 parametric simulation samples generated through Revit and Insight. The study evaluated M5P, Linear Regression (LR), Sequential Minimal Optimization Regression (SMOReg), and RF models, where RF achieved R^2 values above 0.97 with mean errors below 5%. However, the framework focused only on office buildings in a single climatic region and excluded real-world operational datasets.

Wei et al. [11] presented a Sparrow Search Algorithm (SSA)-optimized Bidirectional-LSTM framework with SHapley Additive exPlanations (SHAP) for short-term Heating, Ventilation, and Air Conditioning (HVAC) load forecasting in industrial structures. The study utilized real-time 5-minute operational data collected across four seasons from an industrial facility, incorporating a 17-dimensional feature set containing environmental variables, historical load patterns, and temporal indicators.

The SSA-BiLSTM model achieved a 0.965 of R^2 value with an RMSE of 1.20 kW during winter testing and maintained R^2 values above 0.93 under cross-seasonal conditions. SHAP analysis identified historical load inertia and outdoor temperature as dominant factors affecting prediction performance. However, the framework focused primarily on time-series HVAC forecasting and excluded geometric building parameters and whole-building thermal load estimation.

Zhangabay et al. [12] developed an experimental and computational study on thermal characteristics of an adaptive outer wall envelope having an air layer with controllable properties for residential and public buildings in southern Kazakhstan. Temperature distribution, heat flux, air permeability parameters, and operational regimes were obtained for winter and summer conditions. The most effective Scheme 3/50/75/50 was raised temperatures by 1.5-2.3 °C in winter, reduced wall heat flux by 12-18%, and decrease summer thermal loads by 8-14%. This study considered particular climatic conditions without examining predictive models.

Baset and Jradi [13] developed a data-driven approach for predicting surface-level heat flux and prioritizing the retrofitting of building envelope by employing XGBoost and MLP models. The study considered hourly thermal and environmental data generated through simulations from Danish residential and office buildings, such as indoor air temperature, outdoor air temperature, surface temperature, heating energy consumption, solar radiation, and geometrical parameters.

While XGBoost delivered results in terms of predictive accuracy, RMSE of 11.24 W, MAE of 5.5 W, and R^2 of 0.92, it exhibited stability in residual performance for different ranges of heat fluxes. This approach successfully selected high-impact retrofit surfaces, resulting in an annual heating energy reduction of about 15 GJ. Nevertheless, this research was mainly concerned with heat loss conditions in the winter season only.

Zhangabay et al. [14] presented a numerical optimization study on Suspended Ventilated Facade Systems (SVFS) to evaluate the effect of bracket spacing on structural and thermal performance under Kazakhstan climatic conditions. The study employed Finite Element (FE) models with five simulation series using bracket and bracket offsets of 150-200 mm under static, wind, seismic, and icing loads. The dataset consisted of simulated stress, displacement, and thermal nonuniformity responses across representative climate zones. Results showed that increasing bracket spacing decreased the thermal nonuniformity coefficient from 8.33% to 3.0%, while stresses remained below 75% of yield strength. The optimal spacing range was 800×800 to 1000×1000 mm. However, long-term creep, fatigue effects, and experimental validation were not included.

Karimi et al. [15] developed an integrated framework for evaluating the thermal resilience of residential structures in Madrid under future climate stress. The study combined Energy Plus (EP) simulation, ML, and Genetic Algorithm (GA) optimization using twenty residential building archetypes with localized weather files adjusted for Urban Heat Island (UHI) and heatwave conditions under. Results indicated that future summer temperatures could rise by about 3.5 °C, leading to nearly doubled cooling demand. Compact and well-oriented structures attained up to 27% lower Energy Use Intensity (EUI), while optimized designs reduced EUI by 18% and Operational Carbon Intensity (OCI) by 22%. However, occupancy behavior and techno-economic factors were not included.

Magnavaca et al. [16] presented a BIM ML framework for early-stage prediction of office building energy and carbon performance. The dataset included 14 input variables related to geometry, envelope, systems, and schedules, with five outputs: EUI, Operational Carbon (OC), OE, Total Carbon (TC) and Embodied Carbon (EC). LR, Model Tree (M5P),

SMO, and RF were tested. RF achieved a better R^2 . However, the framework focused on office buildings and limited typological diversity.

Muhič et al. [17] introduced a sensitivity analysis model using the Transient System Simulation Tool (TRNSYS) to examine the influence of building geometry and envelope parameters on annual thermal demand. The study used simulation data from three theoretical multi-residential buildings located in Ljubljana, Slovenia. Results showed that reducing the g-value from 0.62 to 0.22 changed qH, nd by 20-25% and reduced qC, nd by about 95%. Buildings with lower BSF showed lower sensitivity to parameter variation. However, the study was limited to theoretical buildings and one climatic region.

Cao et al. [18] developed a zonal sensor-based coupled daylighting-thermal simulation approach to assess the effects of geometric variables on annual building energy consumption. The dataset consisted of various cases with different building footprints area, floor heights, WWR, window sill heights, and two levels of envelope performance under severe cold, temperate, hot summer-warm winter, cold, and hot summer-cold winter climates.

IQR, ESR, and SA were utilized for analysis. The findings revealed that WWR was the most sensitive variable in terms of EUI, with 41.19% sensitivity, whereas floor height was the least sensitive, with 5.65% sensitivity. However, this research relied heavily on simulations without considering any real-life building data or machine learning techniques.

Chen et al. [19] suggested a data-driven approach to predict Thermal Load by training models like RF and LSTM on simulation data obtained from Energy Plus. The model considered office building prototype models, with several combinations of inputs, which include weather, operation, and building parameters. An R^2 score of 0.9482 and 0.9267 was obtained from RF and LSTM models. It was found that the data-driven method was helpful to avoid complexity and time requirements in physics-based simulations for predicting Thermal Load. Nevertheless, this research used simulation data of office buildings only, without any exploration of attention-based deep tabular learning and feature interactions to predict both HL and CL simultaneously.

Abdel-Jaber and Dirks [20] developed a model with an interpretable ML approach based on the classification of residential building thermal loads from the Energy Efficiency Dataset. The study examined kNN, DT-C4.5, Neural Network (NN), SVM, NB and RI-RIPPER. This dataset includes geometrical and envelope attributes, namely RA, WA, SA, RC, OR, H, and GD, where HL and CL were the outcome. Precision, recall, and accuracy were found satisfactory when RI and DT were implemented in addition to generating easily understandable decision rules. The influential input

parameters include RA and SA. Classification was performed, and DL technique was not applied.

Slowik and Moldovan [21] introduced the Multi-Objective Plum Tree Algorithm (MOPTA) that combines model selection and hyperparameter optimization while predicting building thermal loads. The dataset applied in the paper was the Energy Efficiency Dataset, which comprises geometric and envelope data with HL and CL as the output features. ETR, GBR, and RFR were configured with five hyperparameters each to optimize their performance. The results indicated a reduction in RMSE for heating to 0.035719 and cooling to 0.076197 compared to individual regressors' RMSE. Nonetheless, MOPTA was based only on tree models and neglected deep learning models.

Mahmood et al. [22] designed a framework for predicting thermal demand of green buildings using ML algorithm based on active learning approach through Energy Efficiency Dataset. Various algorithms such as RF, DT, GB, XGBoost, CatBoost (CB), LGBM, KNN, and LR were compared and analyzed. The CBR-AL framework was used for predicting cooling and heating demands in green buildings. Prediction scores achieved for cooling and for heating, which outperformed other baselines. But there was no deep attention-based tabular architecture used in the paper.

Alharbi et al. [23] developed an ANN-WWPA hybrid modelling system that utilized ANNs along with Waterwheel Plant Algorithm (WWPA) for predicting residential building thermal loads. In this study, the MLPRegressor algorithm was used to analyze the Energy Efficiency Dataset. The use of WWPA enabled automatic hyperparameter optimization. This method produced satisfactory results as far as evaluation metrics are concerned, and determine the design variables influencing thermal load. However, the use of high-quality benchmarking data and narrow datasets in evaluating the system were the key shortcoming of the modelling framework. Building physics, IoT-based monitoring systems, and data analytics have been developed in recent years, making intelligent building energy management a quick development. Combining machine learning with the building design parameters can provide an accurate prediction of thermal load in the early design phase, and the machine learning can also be integrated with the operational data collected by the IoT system, which can help optimize energy use in smart buildings in real-time. Thus, interpretable deep learning models for structured building data will further enhance the prediction accuracy and help in intelligent decision-making for sustainable and energy-efficient building design.

2.1. Research Gap

Recent studies on building thermal load prediction limited to simulation-based models, classical ML methods, optimization-enhanced regressions, and forecasting techniques that utilize hybrid approaches in predicting the

energy performance of buildings [9, 10, 16, 21]. Some previous research works examined adaptive façade systems, suspended ventilated facades, thermal resilience assessments, and geometric optimizations to enhance thermal efficiency and passivity throughout the seasons; nevertheless, the said prior studies paid more attention to component-level and simulation-level analysis instead of developing a generalized model for both HL and CL predictions via structured building data [12, 17, 18]. Moreover, ML-based interpretable models, ensemble regressions, and shallow neural networks were considered in predicting building thermal load based on the Energy Efficiency Dataset; nonetheless, there is still a lack of knowledge regarding nonlinear interaction learning in geometric and envelope variables [20, 23]. These models further focused on model efficiency and hyper-parameter tuning with less emphasis on adaptive feature selection, feature weighting based on context, and attention-based dependency learning among SA, RC, orientation, GA, and OH [19, 21, 22]. Additionally, some investigations were carried out under controlled climatic environments, datasets of specific offices, simulated settings, or HVAC operation during particular seasons, which hindered the development of more robust systems [9-11, 13, 17]. The proposed hybrid TabNet-ResMLP framework overcomes some of the unresolved limitations of the existing approaches. To address these problems, TabNet implements attention-guided adaptive feature selection, automatically discovering the most informative geometric and envelope attributes during training; and ResMLP is able to model complex nonlinear relationships by performing residual learning. Furthermore, the proposed framework not only predicts both heating load and cooling load within a single architecture but also adds feature importance, sensitivity analysis, and interaction analysis to enhance interpretability of the model. The proposed approach extends the existing thermal load prediction approaches by integrating attention-based deep tabular learning, residual nonlinear regression and explainable analysis into a single prediction framework.

3. Materials and Methods

The general flow of work involved in this research starts with the collection of data. First, EDA is done to assess the data distribution, explore relationships among the variables, and analyze the behavior of heating and cooling loads. This will be followed by data preprocessing, where the data is cleaned, normalized, and prepared for framework implementation. The resulting data set will be divided into training, validation, and testing sets to facilitate the development and assessment of the framework's accuracy and effectiveness. In the hybrid framework approach, the TabNet used to select and feature selection, while the ResMLP capture nonlinear relationships in the data to predict HL and CL. Finally, the predictions of the framework will be statistically analyzed and assessed to interpret the effects of geometrical and envelope parameters on thermal load behavior in buildings, as shown in Figure 1.

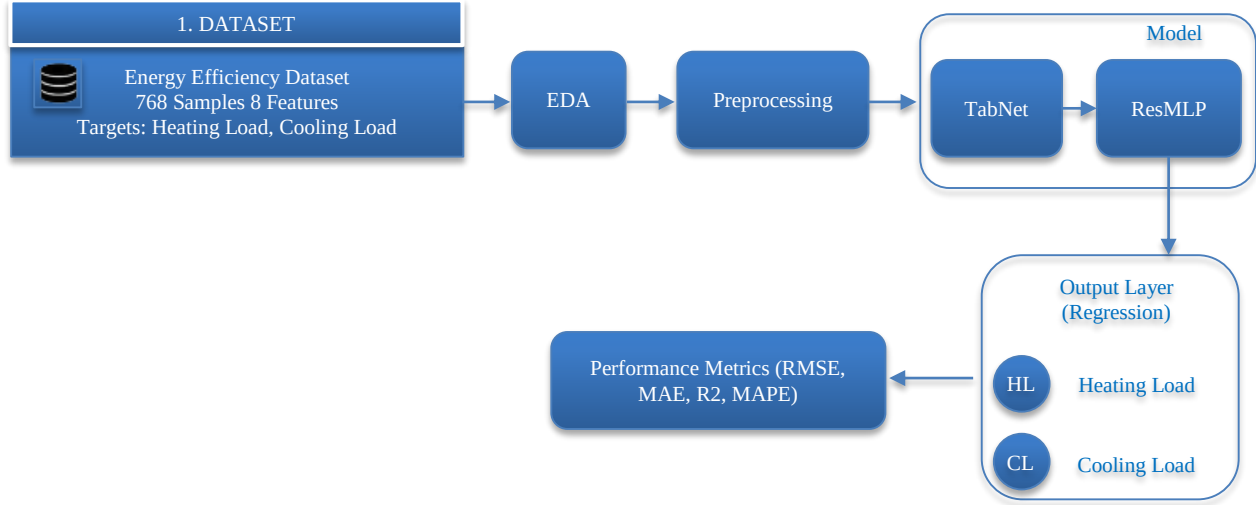


Fig. 1 Block diagram of proposed model

3.1. Dataset

The Energy Efficiency dataset employed for developing this model taken from the Kaggle and the UCI ML Repository [24]. The dataset has created using the simulation of energy efficiency performance analysis carried out on prototypes of residential buildings designed on Ecotect (ECT). Multiple building designs analyzed based on different geometrical conditions. There is a total of 768 instances of building designs included in the database; each one is a unique combination of certain parameters like shape, orientation, glazing ratio, and glazing distribution. The total number of variables present in the dataset is of 8 input variables and two continuous output variables. The input features include 768 samples of residential building designs having eight geometric

and envelope-related input variables, including RC, SA, WA, RA, OH, OR, GA, and GAD. The output variables include HL and CL, indicating the thermal energy required for maintaining the comfort of residential buildings. This dataset is commonly used for evaluating the performance of predictive models owing to its well-structured tabular form depicting the relationship between the building design attributes and thermal loads' performance. The input variables selected are important geometric and envelope parameters that greatly affect building thermal performance. The data set is simulation-based but based on realistic residential building configurations and has become widely used as a standard data set for testing building energy prediction models.

	X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	0.764167	671.708333	318.500000	176.604167	5.250000	3.500000	0.234375	2.81250	22.307201	24.587760
std	0.105777	88.086116	43.626481	45.165950	1.75114	1.118763	0.133221	1.55096	10.090196	9.513306
min	0.620000	514.500000	245.000000	110.250000	3.500000	2.000000	0.000000	0.000000	6.010000	10.900000
25%	0.682500	606.375000	294.000000	140.875000	3.500000	2.750000	0.100000	1.75000	12.992500	15.620000
50%	0.750000	673.750000	318.500000	183.750000	5.250000	3.500000	0.250000	3.00000	18.950000	22.080000
75%	0.830000	741.125000	343.000000	220.500000	7.000000	4.250000	0.400000	4.00000	31.667500	33.132500
max	0.980000	808.500000	416.500000	220.500000	7.000000	5.000000	0.400000	5.00000	43.100000	48.030000

Fig. 2 Sample dataset

3.2. Exploratory Data Analysis

EDA is a key initial process in ML and DL investigations that allows gaining insight into the distributions, statistics, and dependencies between input and output features prior to constructing a predictive model. In this research, EDA was performed to investigate the geometric and envelope-related features, feature dependency, and their impact on HL and CL. The three types of analysis were performed, namely statistical analysis, analysis of the relationship between the features, and correlation analysis. Figure 3 shows the heatmap of the correlation between the input features and their relationships with HL and CL. According to the results, the overall height

demonstrated a positive correlation with HL (0.89) and CL (0.90), while the roof area showed a negative correlation with HL (-0.86) and CL (-0.86). At the same time, relative compactness positively correlated with thermal loads moderately, while orientation and glazing area distribution affected them much less. Finally, HL and CL contains mutual correlation equal to 0.98, which means that their trends are very similar. Overall, based on the results of EDA, the existence of nonlinear and interdependent relationships between the building parameters was proven, which justifies using TabNet-ResMLP for prediction of the loads.

3.3. Data Preprocessing

The preprocessing was done to format the unstructured dataset on building energy into a structured form that used to train the proposed DL model, TabNet-ResMLP. First, the dataset was checked for any missing, inconsistent, or duplicate values and observed that the dataset was intact with no null or duplicate records. Thereafter, the input variables were separated from the target outputs, where the feature matrix consisted of eight geometric and envelope attributes, while the target matrix contained HL and CL. Since the variables were measured on different numerical scales, feature normalization was applied using Z-score standardization to improve training stability and convergence, as expressed in Equation (1).

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

where X signifies the original feature value, μ signifies the mean of the feature, σ indicates the standard deviation, and X' signifies the standardized output. After normalization, the processed dataset was randomly divided into training, validation, and testing subsets using a 70:15:15 ratio to ensure unbiased model assessment. Only Z-score normalization was performed to normalize features' scales, that is, to make them comparable in order to ensure a stable model training process and to facilitate the reproduction of the results, as there are no missing or duplicated values in the dataset.

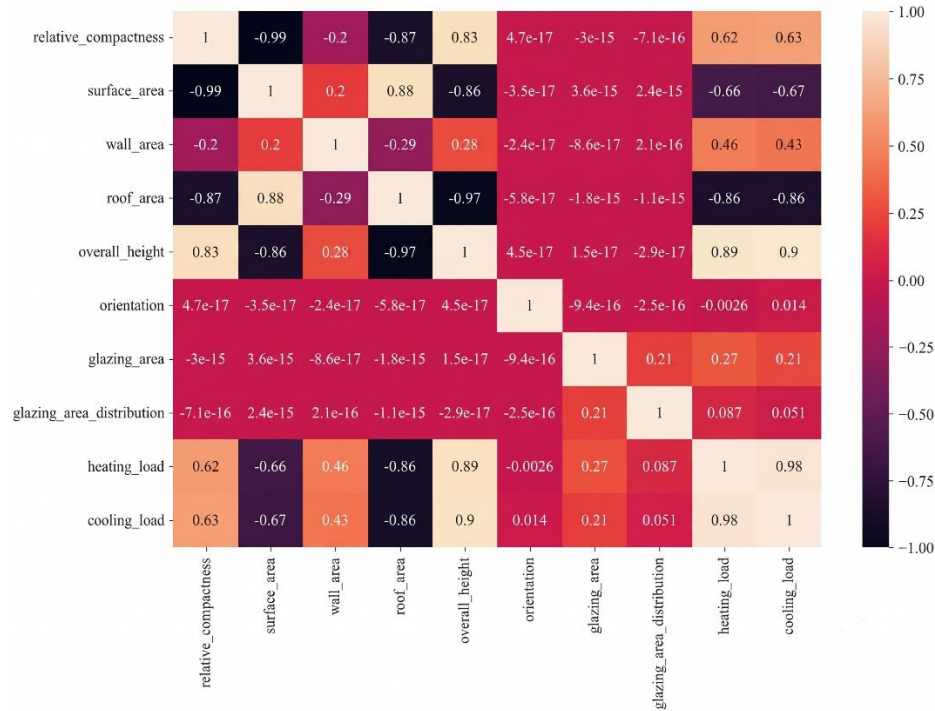


Fig. 3 Correlation heatmap of input features and thermal load variables

3.4. Model Development

Model development was carried out to construct an effective predictive framework for estimating building thermal load using geometric and envelope attributes. In this study, a hybrid TabNet-ResMLP model was developed by integrating TabNet for feature selection and representation learning with Residual Multilayer Perceptron (ResMLP) for nonlinear regression prediction. The combined architecture was designed to improve learning efficiency, prediction accuracy, and generalization performance for HL and CL estimation. The proposed hybrid approach treats the eight geometric and envelope attributes, including: (Relative Compactness, Surface Area, Wall Area, Roof Area, Overall Height, Orientation, Glazing Area, Glazing Area Distribution) as a combined feature vector. The attributes are initially normalized and passed to TabNet for encoding, which

computes attention masks one by one, which are used to select the most informative attributes at each decision point. TabNet does not give equal weight to all attributes, but dynamically learns the relevance of features based on the prediction task. These latent feature representations are then passed to the ResMLP module for nonlinear regression with efficient training, yet retaining informative feature representations learned by the encoder, thanks to residual connections. The proposed architecture is thus adaptive feature selection with residual learning to capture the complex interactions among building design parameters that affect the heating and cooling loads.

3.4.1. TabNet

TabNet is a DL network specifically developed for structured tabular datasets, where a sequential attention

mechanism is employed to select informative structures at each decision step. Unlike conventional neural networks that process all variables simultaneously, TabNet dynamically focuses on the most relevant attributes through sparse feature masks, thereby improving interpretability and predictive efficiency. The architecture consists of four key components: an input feature layer, an attentive transformer, a feature transformer, and multiple sequential decision steps. The attentive transformer generates sparse masks to identify important variables, while the feature transformer extracts nonlinear representations using shared and independent fully connected layers with Gated Linear Unit (GLU) activations [25]. The outcomes from all decision steps are aggregated to form the final encoded representation. This property makes TabNet particularly suitable for the present study, where geometric and envelope variables exhibit varying degrees of influence on building thermal load. Figure 4 illustrates the architecture of the proposed TabNet block.

In the proposed framework, TabNet is employed as the initial learning component to extract meaningful latent representations from the eight normalized input variables. The normalized input feature matrix $X \in \mathbb{R}^{n \times d}$, where n denotes the number of samples and $d = 8$ represents the number of features, is provided to the TabNet encoder. At each decision step t , the attentive transformer produces a sparse feature selection mask. M_t , defined as in Equation (2).

$$M_t = \text{sparsemax}(P_t) \quad (2)$$

Where P_t represents the processed feature importance scores, and the sparsemax function produces sparse probability distributions by assigning zero weights to less relevant features, thereby enhancing interpretability. The masked feature representation is then obtained as in Equation (3).

$$X_t = M_t \odot X \quad (3)$$

Where $\odot$ denotes element-wise multiplication. The selected features are subsequently passed through the feature transformer block, which consists of fully connected layers, batch normalization, and GLU activations to learn nonlinear latent representations. The transformed outputs from each decision step are aggregated to form the final encoded representation H , expressed as in Equation (4).

$$H = \sum_{t=1}^T h_t \quad (4)$$

Where h_t denotes the learned representation at decision step t , and T represents the total number of decision steps.

In this study, the TabNet model is configured with a decision dimension of 32, attention dimension of 32, number of decision steps $T = 4$, relaxation factor of 1.5, batch size of 32, and learning rate of 0.001, ensuring stable convergence

and efficient feature selection. Finally, the encoded feature vector generated by TabNet is forwarded to the ResMLP module for predicting HL and CL.

3.4.2. Residual Multilayer Perceptron

The ResMLP is an advanced form of Multilayer Perceptron (MLP) where the incorporation of residual skip connections used to boost the flow of information between layers and ensure stable model training. Classic MLP models might encounter issues such as poor performance with increased depth of the network, owing to the vanishing gradients problem and the inability to represent features properly. In order to solve this issue, ResMLP employs shortcut connections, which allow the learning of residual mapping and thus ensures proper feature representation and easy gradient propagation [26].

ResMLP used as the second learning technique after the TabNet encoder to model the nonlinear relationship between the extracted features and thermal load output. The encoding of the features obtained using TabNet denoted as H . The feature representation is taken as an input for the first dense layer shown in Equation (5).

$$Z_1 = f(W_1 H + b_1) \quad (5)$$

Where W_1 and b_1 characterize trainable weight and bias parameters, respectively, and $f(\cdot)$ denotes the Rectified Linear Unit (ReLU) activation function. The resulting representations are next mapped into the subsequent dense layer, which has a skip connection to the preceding layer, as demonstrated in Equation (6).

$$Z_2 = f(W_2 Z_1 + b_2) + Z_1 \quad (6)$$

Where the addition operation represents the residual shortcut connection.

This formulation ensures consistent dimensionality and enables effective gradient flow while retaining learned feature representations. To prevent overfitting, dropout regularization is applied as in Equation (7).

$$Z_d = \text{Dropout}(Z_2, p) \quad (7)$$

Where p denotes the dropout probability. In this study, the dropout rate is set to 0.2. The processed features are then passed to the output layer for final prediction, as shown in Equation (8).

$$Y = W_o Z_d + b_o \quad (8)$$

Where Y indicates the estimated HL and CL. In the ResMLP architecture, the number of nodes in hidden layers was set to 64 and 32 using the activation function of ReLU. Such a configuration ensured good mappings from input

features to thermal load output. In the proposed approach, the TabNet encoder and ResMLP model were sequentially employed. First, TabNet encoder learned the informative latent representations from geometric and envelope

information through attentive feature processing. Subsequently, the learned feature vector was used in the ResMLP model to estimate HL and CL.

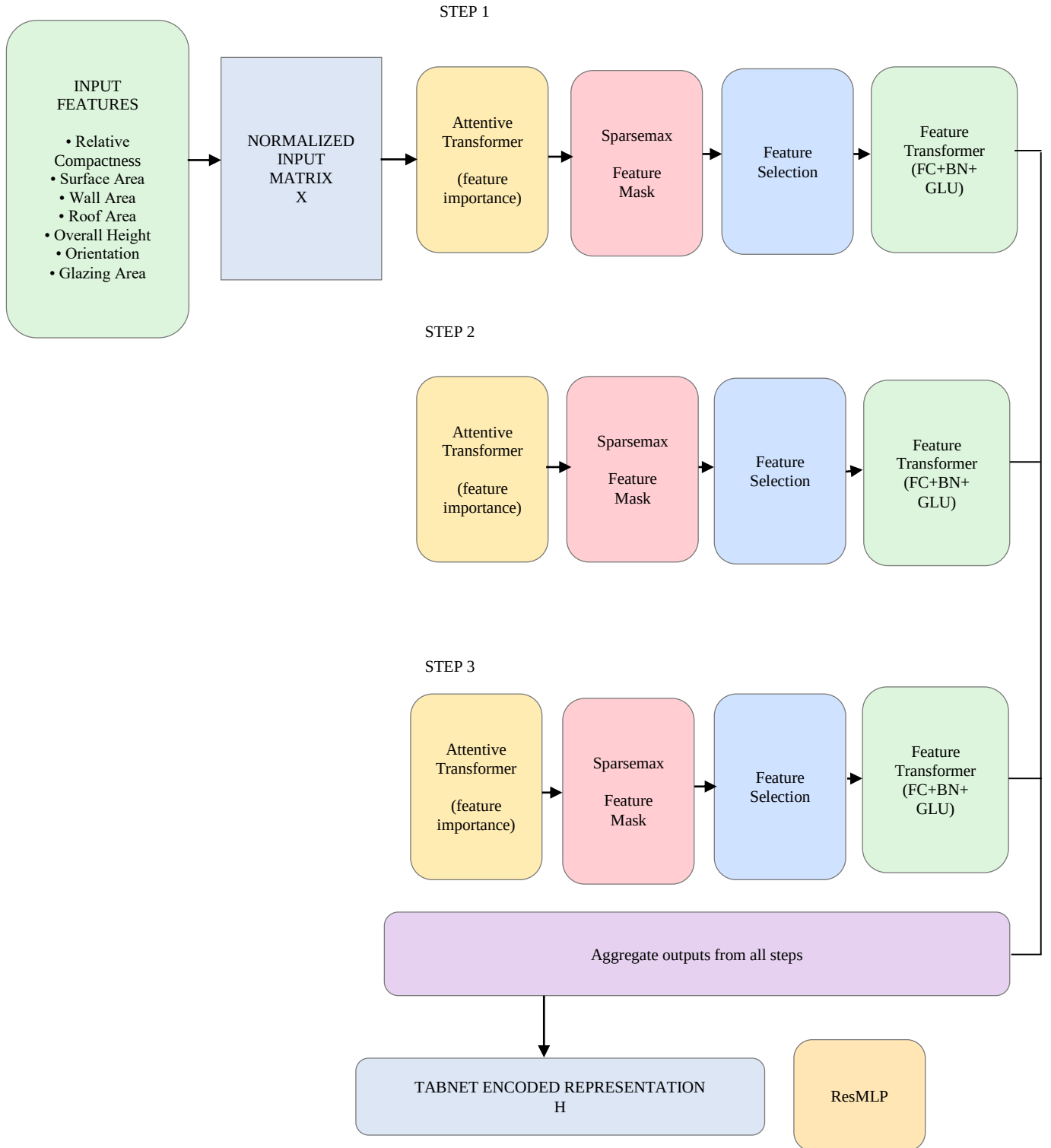


Fig. 4 Architecture of proposed TabNet block

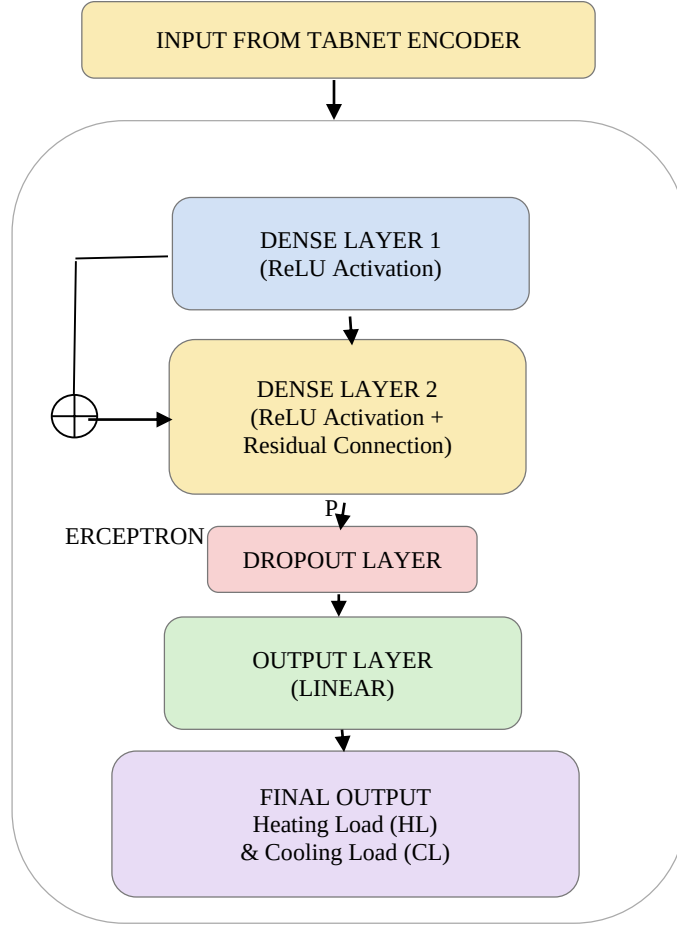


Fig. 5 Proposed architecture of ResMLP

The algorithm of the proposed approach is provided below.

Algorithm: Hybrid TabNet Encoder-ResMLP Model for Thermal Load Prediction

Input:

Building dataset D with features $X \in \mathbb{R}^{n \times 8}$

Output:

Predicted thermal loads $\hat{Y} = \{HL, CL\}$

Begin

Step 1: Data Preparation

Load dataset D with input features and targets (HL, CL).

Perform EDA, normalize features using Z-score.

Dataset Splitting

Step 2: TabNet Encoder - Feature Representation

Initialize TabNet parameters:

Decision dimension $d = 32$

Attention dimension $d_a = 32$

Number of steps $T = 4$

Select important features using a mask

$$M_t = \text{sparsemax}(P_t)$$

Apply the mask to input features.

$$X_t = M_t \odot X$$

Transform selected features

$$h_t = f(X_t)$$

Combine all step outputs:

$$H = h_1 + h_2 + \dots + h_T$$

Step 3: ResMLP - Regression Learning

First transformation:

$$Z_1 = \text{ReLU}(W_1 H + b_1)$$

Second layer with correct residual connection:

$$Z_2 = \text{ReLU}(W_2 Z_1 + b_2) + Z_1$$

Apply dropout:

$$Z_d = \text{Dropout}(Z_2, p = 0.2)$$

Step 4: Model Training

Generate predictions.

$$\hat{Y} = W_o Z_d + b_o$$

Compute loss:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

Step 5: Output

Final predicted values:

$$\hat{Y} = \{HL, CL\}$$

End

The choice of TabNet and ResMLP was driven by the structure of the Energy Efficiency dataset, which consists of tabular data with geometric and envelope properties of buildings. In contrast to CNNs and LSTMs, which are mainly developed for image and sequential data, TabNet is tailored to tabular learning, allowing for improved prediction and interpretability, as it involves an attention-based feature selection mechanism. However, ResMLP complements TabNet because it was able to effectively model the complex nonlinear relationship while maintaining stable training and generalization. TabNet's incorporation of ResMLP with adaptive feature selection is ideal for accurate and interpretable prediction of building thermal loads.

3.5. Simulation Setup

The Hybrid TabNet-ResMLP architecture was developed using Python 3.10 language and the PyTorch DL framework. The computations done within a GPU-assisted computational environment utilizing Google Colab services. All necessary data processing and analysis tasks were done using commonly used scientific packages such as NumPy, Pandas, and Scikit-learn. Model building and training were done via the PyTorch framework. Hyperparameters are preset configurations that dictate the learning process and greatly affect the performance and convergence of models. Appropriate selection of these parameters is essential for achieving stable training and improved predictive accuracy.

Hyperparameters were selected experimentally based on validation performance. Model validation was performed using a 70:15:15 train-validation-test split. The validation set was utilized to tune the hyperparameters and stop the training prematurely, and the independent test set was used to make the final evaluation. Moreover, k-fold cross-validation method was implemented to evaluate the robustness and generalization of the model. The proposed model was further compared with the MLR, SVR, RF, ANN, and standalone TabNet, with the same evaluation metrics. The hyperparameters adopted in the proposed framework are shown in Table 1.

Table 1. Hyperparameters used in the proposed TabNet-ResMLP model

Parameter	Value
Batch Size	32
Number of Epochs	150
Activation Function	ReLU
Decision Steps (TabNet)	4
Optimizer	Adam
Decision Dimension	32
Attention Dimension	32
Dropout Rate	0.2
Train: Validation: Test Ratio	70:15:15
Loss Function	MSE
Early Stopping	Enabled
Learning Rate	0.001

4. Results and Discussion

4.1. Model Performance Evaluation

The prediction capabilities of the developed model (TabNet-ResMLP) were quantitatively estimated using typical regression indicators, such as RMSE, MAE, R² and MAPE. All these indices reflect the quality of the model's ability to estimate building heat consumption. The formula for the RMSE calculation is represented below in Equation (9).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

The MAE signifies the average absolute variance among predicted and actual values, as defined in Equation (10).

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (10)$$

The R² evaluates the proportion of change explained by the method, as expressed in Equation (11).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (11)$$

The MAPE quantifies the percentage deviation between predicted and actual values, as defined in Equation (12).

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (12)$$

The obtained results show that the designed model achieves high prediction accuracy with regards to HL and CL. In particular, the proposed model achieves an R² of 0.98 and 0.97 for HL and CL, respectively, which means that there is a large share of variability explained by the input factors.

Moreover, the low values of RMSE and MAE reveal that there is a difference between estimated and measured results, meaning that thermal loads are estimated precisely. Performance results are presented in Table 2.

Table 2. Performance metrics of proposed TabNet-ResMLP model

Metric	HL Value	CL Value
RMSE (kW)	1.65	1.95
MAE (kW)	1.12	1.38
R ²	0.98	0.97
MAPE (%)	6.0	7.1

Figure 6 presents the comparison among actual and predicted values for (a) HL and (b) CL. The results show that the predicted values closely align with the ideal reference line, representing accurate estimation of thermal loads. The dense clustering of points along the diagonal reflects minimal prediction error and strong agreement between observed and predicted values.

Figure 7 illustrates the distribution of residual errors for (a) HL and (b) CL. The residuals are symmetrically distributed around zero with near-zero mean values, indicating the

absence of systematic bias. The bell-shaped distribution further suggests consistent model behavior with controlled variability in prediction errors.

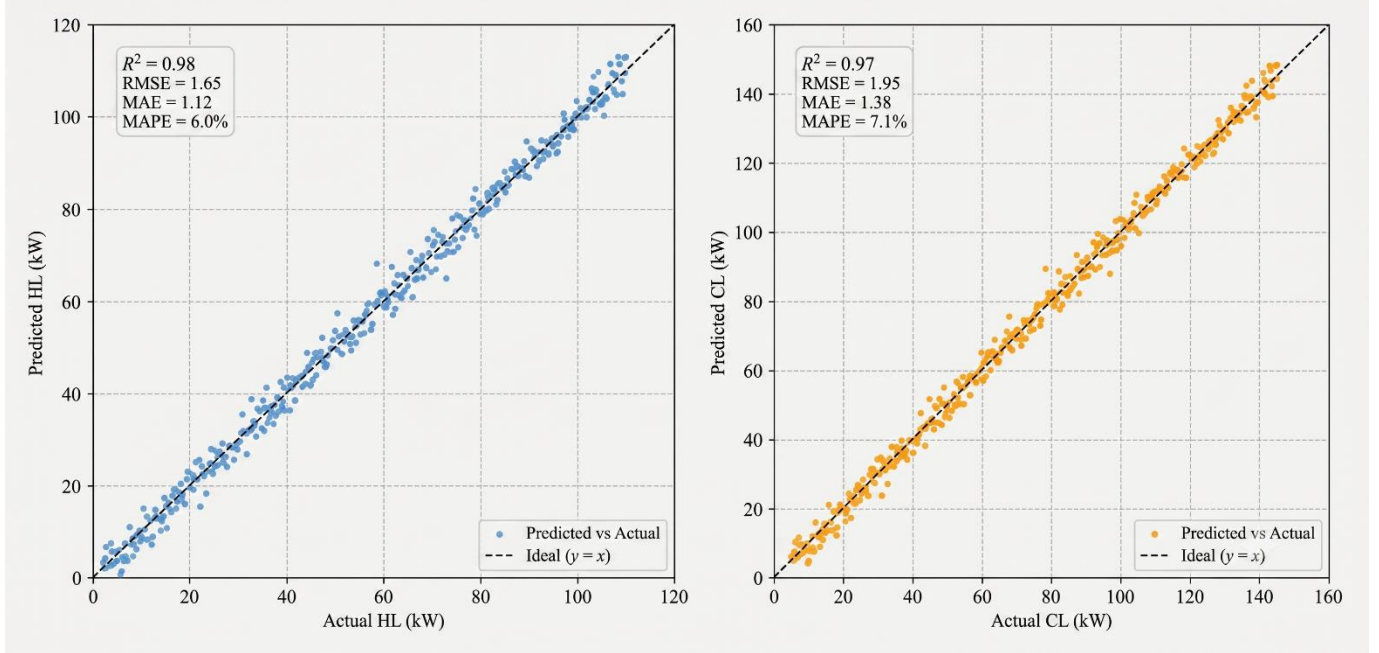


Fig. 6 Comparison between actual and predicted values for thermal loads

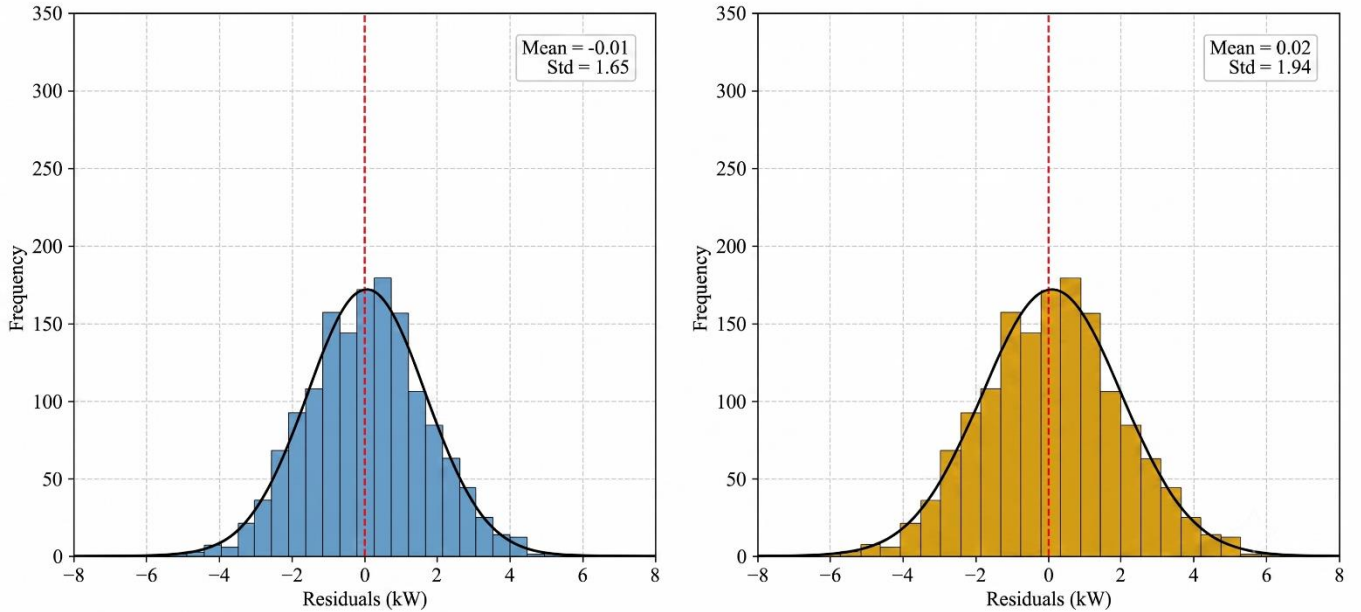


Fig. 7 Residual error distribution for Heating and Cooling Loads

4.2. Baseline Comparison

The prediction power of the proposed hybrid TabNet-ResMLP model was compared to some baseline models, such as MLR, SVR, RF, ANN, and TabNet alone, using RMSE, MAE, R^2 , and MAPE criteria in order to verify a fair

comparison between all techniques. The comparison results shown in Figure 8 revealed that the developed model performed better than other models based on minimal prediction errors and maximum value of the coefficient of determination. For example, the model reached an R^2 score of

0.98 and 0.97 for HL and CL, respectively, indicating higher predictive ability. The improvement in prediction was due to two main factors. First, the feature selection process allowed extracting relevant feature representation and second, the nonlinear regression led to the learning of complicated interactions between input variables and thermal loads. The traditional modelling approaches, like MLR and SVR, had higher prediction errors while RF and ANN were more accurate. However, these models outperform the proposed hybrid approach in terms of predictability. Even the TabNet alone model performs well in the prediction task, yet its combination with the ResMLP yielded additional improvement in prediction power. Overall, the outcomes

establish that the proposed TabNet-ResMLP model delivers more accurate and consistent predictions of building thermal loads compared to the baseline models. The proposed TabNet-ResMLP framework recorded the lowest prediction errors and highest R^2 values for both heating and cooling loads when compared to all the baseline models. The conventional methods (MLR and SVR) failed to identify the nonlinear relationships, and the RF and ANN models did not have adaptive attention-based feature selection. While TabNet was able to learn features that were interpretable, it was found that combining TabNet with ResMLP enhanced the nonlinear regression capability and led to better prediction accuracy and robustness of the models.

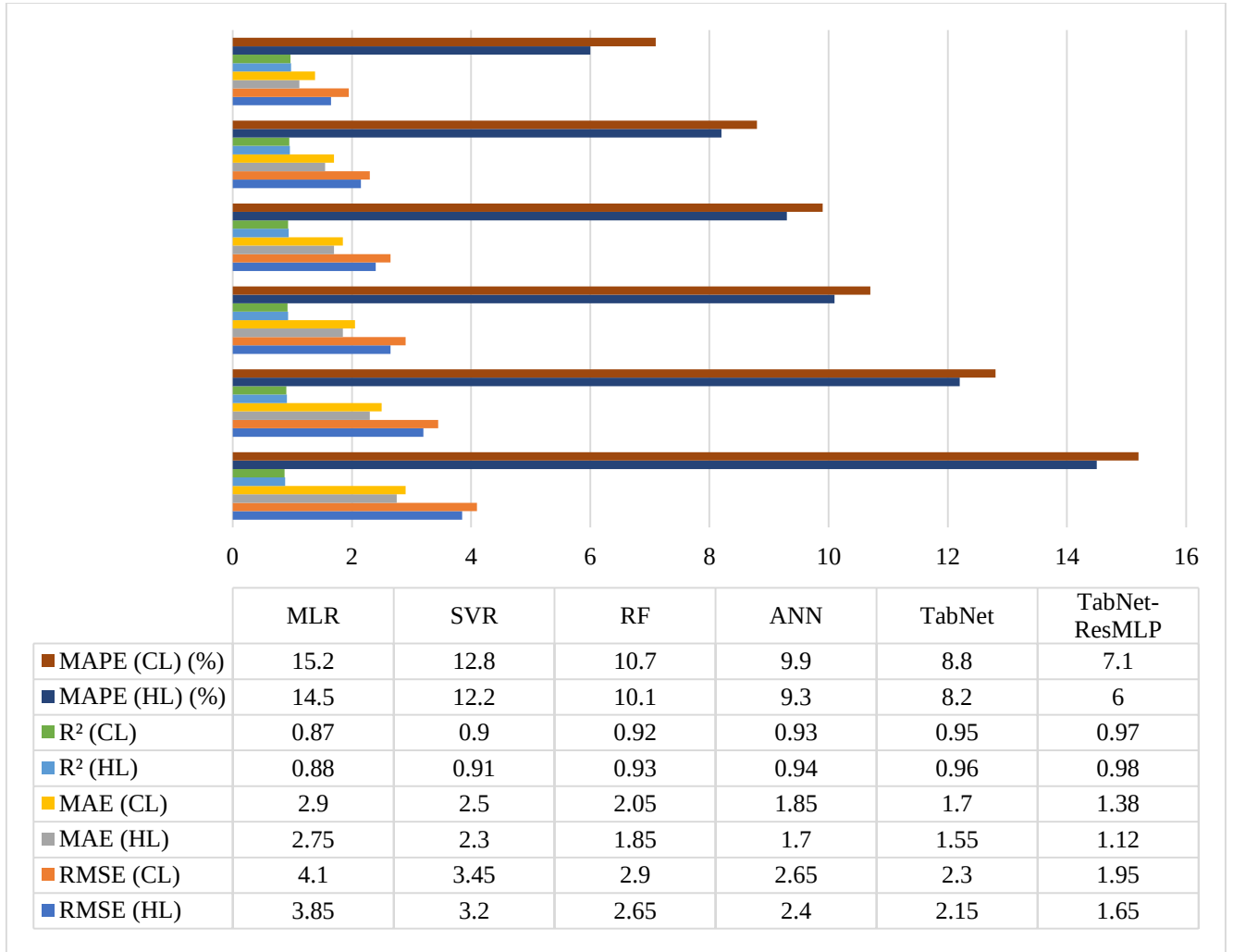


Fig. 8 Baseline comparison of models for thermal load prediction

4.3. Ablation Study

The ablation experiments were conducted in order to analyze the influence of each element in the proposed framework on model performance by applying various model architectures under the same settings. The results shown in Table 3 reveal that the model without attention mechanisms (i.e., ResMLP only) produced RMSE scores of 2.85 (HL) and

3.10 (CL) with respective R^2 of 0.91 and 0.90. It is clear that the performance is relatively weak because feature selection is not used in this case. Meanwhile, the TabNet architecture resulted in RMSE values of 2.15 (HL) and 2.30 (CL) together with R^2 scores of 0.96 and 0.95, respectively, which implies the efficiency of attentive learning. More advanced performance can be observed with the combination of TabNet

and the regular MLP architecture: RMSE values of 1.95 (HL) and 2.10 (CL) were achieved with R^2 values of 0.97 and 0.96, respectively. Nevertheless, the proposed TabNet-ResMLP

framework yielded the best results in terms of the lowest RMSE values of 1.65 (HL) and 1.95 (CL) and the highest R^2 values of 0.98 and 0.97.

Table 3. Ablation study

Model Variant	RMSE (HL)	RMSE (CL)	MAE (HL)	MAE (CL)	R^2 (HL)	R^2 (CL)
ResMLP Only	2.85	3.10	2.05	2.25	0.91	0.90
TabNet Only	2.15	2.30	1.55	1.70	0.96	0.95
TabNet + MLP	1.95	2.10	1.40	1.55	0.97	0.96
TabNet-ResMLP (Proposed)	1.65	1.95	1.12	1.38	0.98	0.97

4.4. K-Fold Cross Validation

The performance and robustness of the proposed TabNet-ResMLP architecture were further analyzed through K-Fold Cross Validation (CV). In this experiment, the CV was carried out using a 5-fold cross-validation technique, wherein the entire dataset was divided into five equal parts. For each run, four parts were selected for training purposes, while the rest was used for validation, ensuring that all data were used for both training and validation phases during each fold. The results obtained through the cross-validation experiment are summarized in Table 4. It is apparent from the above results

that the methodology has yielded consistent results for each of the folds considered, with RMSE for HL in the range of 1.62 - 1.70, while for CL, the value lies between 1.90 - 1.98. On the other hand, the R^2 scores have been quite consistent, varying between 0.97 and 0.98 for HL and between 0.96 and 0.97 for CL. Consistency in the values of RMSE and R^2 indicates that there are no signs of overfitting in the architecture, which makes it very reliable and stable. The robustness of the proposed method in terms of its stability for different folds is shown in Figure 9, which shows that RMSE scores for HL and CL vary little, thus demonstrating good consistency.

Table 4. K-fold cross-validation results

Fold	RMSE (HL)	RMSE (CL)	R^2 (HL)	R^2 (CL)
Fold 1	1.68	1.95	0.98	0.97
Fold 2	1.65	1.92	0.98	0.97
Fold 3	1.70	1.98	0.97	0.96
Fold 4	1.62	1.90	0.98	0.97
Fold 5	1.66	1.94	0.98	0.97
Mean	1.66	1.94	0.98	0.97
Std Dev	0.03	0.03	0.004	0.004

K-Fold Cross-Validation RMSE Distribution

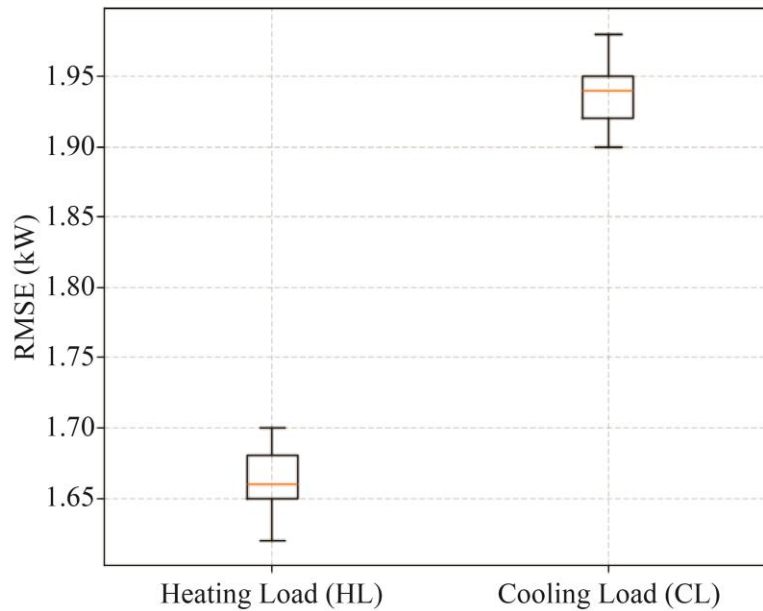


Fig. 9 K-fold cross-validation performance

4.5. Feature Importance Analysis

The individual contributions of input variables in predicting the thermal loads of buildings were evaluated using the concept of feature importance. Feature importance, in the developed model, is defined through the attention technique employed by TabNet. This technique weighs the importance of different input variables depending on their level of influence during the learning process. The results of the feature importance analysis are presented in Figure 10 below. RC, OH, and SA emerged as the three most important input variables for predicting HL and CL. Relative Compactness was found to have the highest influence since it plays a critical

role in managing the heat transfer properties of the building. Conversely, attributes like OA and GAD were found to be of less significance, indicating their minimal influence on thermal loading prediction based on the dataset used. The glazing area was considered moderately significant owing to its contribution towards heat absorption from the sun and energy transfer. In general, it can be noted that the geometry-related attributes have played an important part in determining the energy performance of buildings. The capability of the proposed model to assess the significance of each attribute makes it practical.

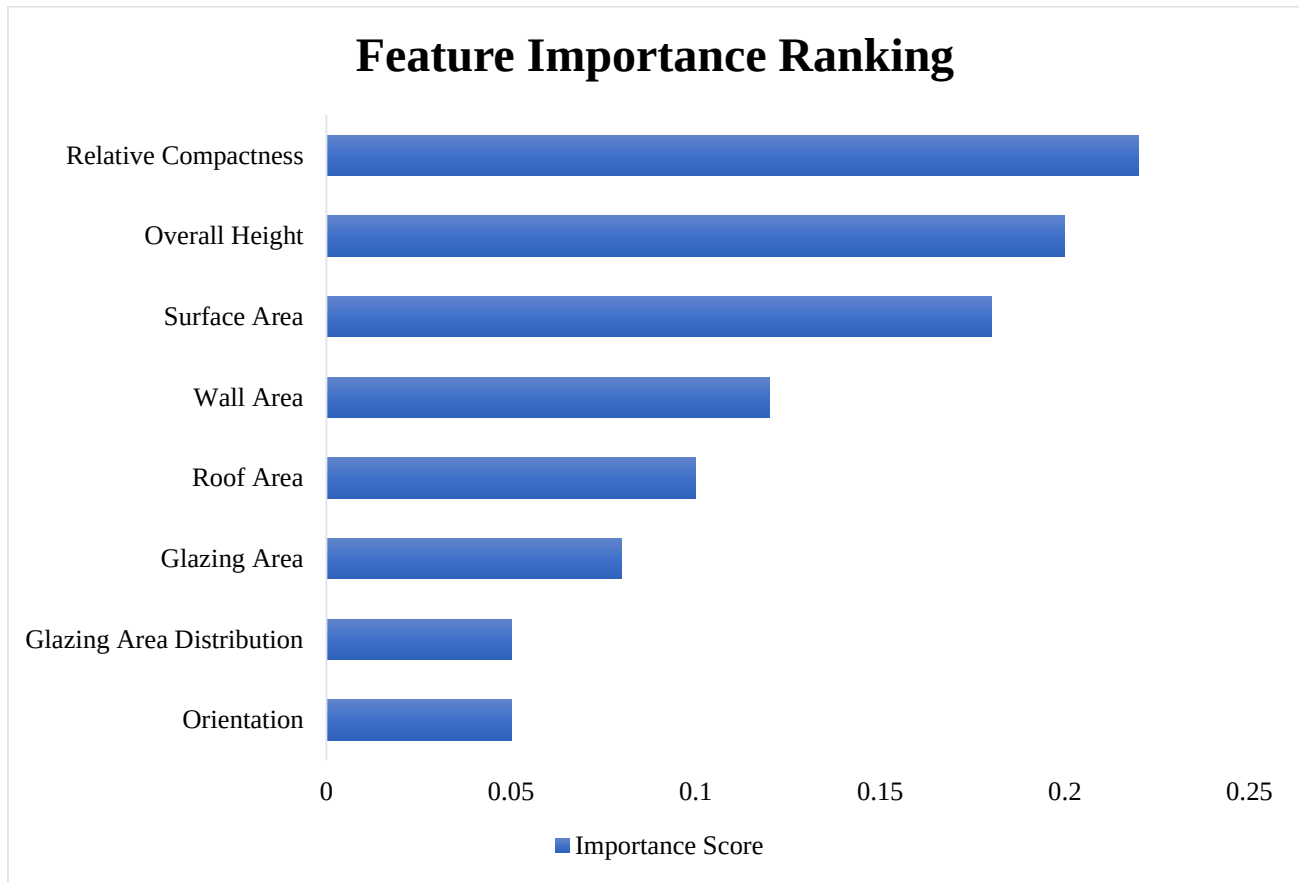


Fig. 10 Feature importance ranking of input variables for thermal load prediction obtained from the proposed TabNet-ResMLP model

4.6. Sensitivity Analysis

Sensitivity analysis was performed to understand the effects of the single input parameter on thermal load calculations when other variables were kept constant. According to the outcomes depicted in Figure 11, the relative compactness, total building height, and surface area had the highest influence on the thermal loads of HL and CL. Relative compactness was found to be responsible for a drop of 18-22% in HL and 12-15% in cooling loads due to improved thermal performance. In contrast, an increase in building height caused a 10-14% increment in HL and 8-12% increase in CL because of increased exposure to heat exchange. In addition, surface

area also showed a contribution of 12-16% in thermal loads due to increased building envelope size. Orientation and area of glazing showed low sensitivity, which accounted for less than 5% variation in both heating load and cooling load. Area of glazing contains a significant influence, especially on cooling load, where it resulted into about 8-11% increase in cooling load because of higher solar heat gain. From the above, evident that geometric parameters play major role in influencing thermal performance of a building. Consistent behavior of results in HL and CL indicates that the proposed approach successfully established a relationship between design parameters and energy requirement.

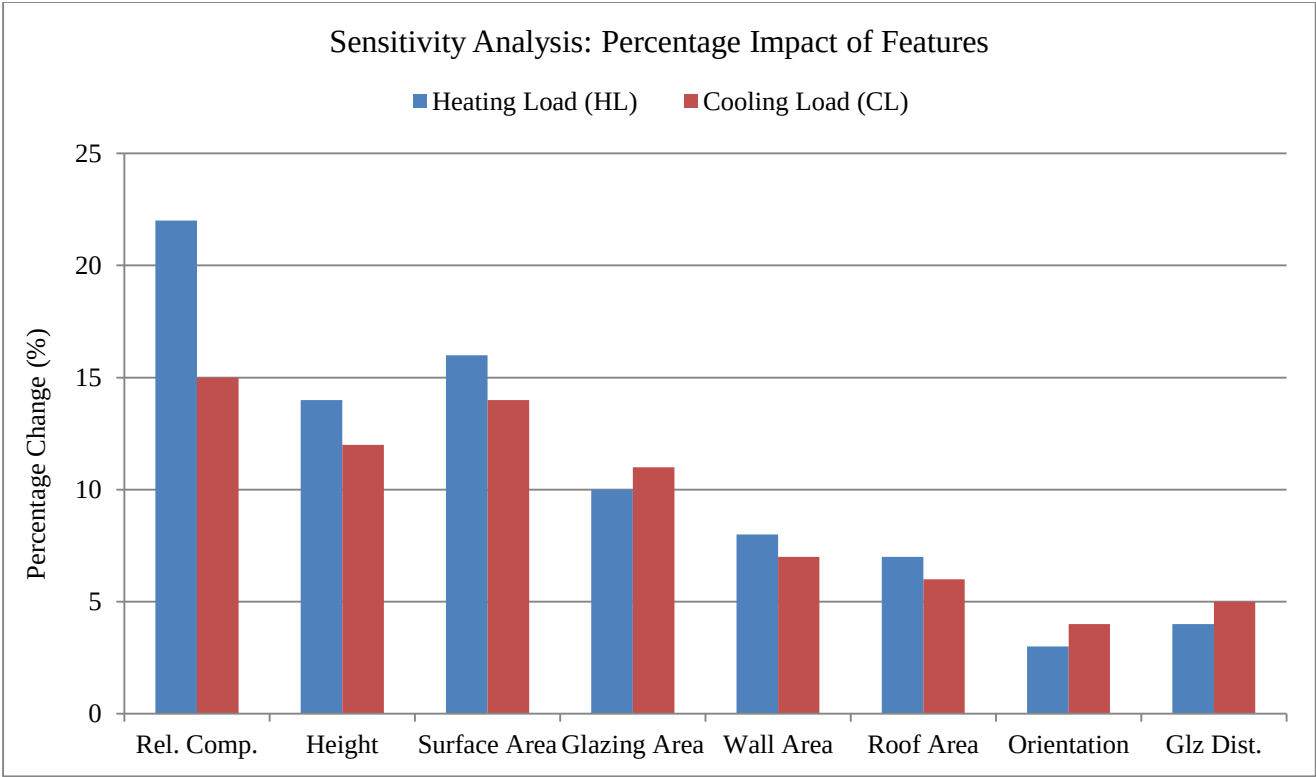


Fig. 11 Percentage change in HL and CL with respect to variations in input features, illustrating the relative sensitivity of each parameter

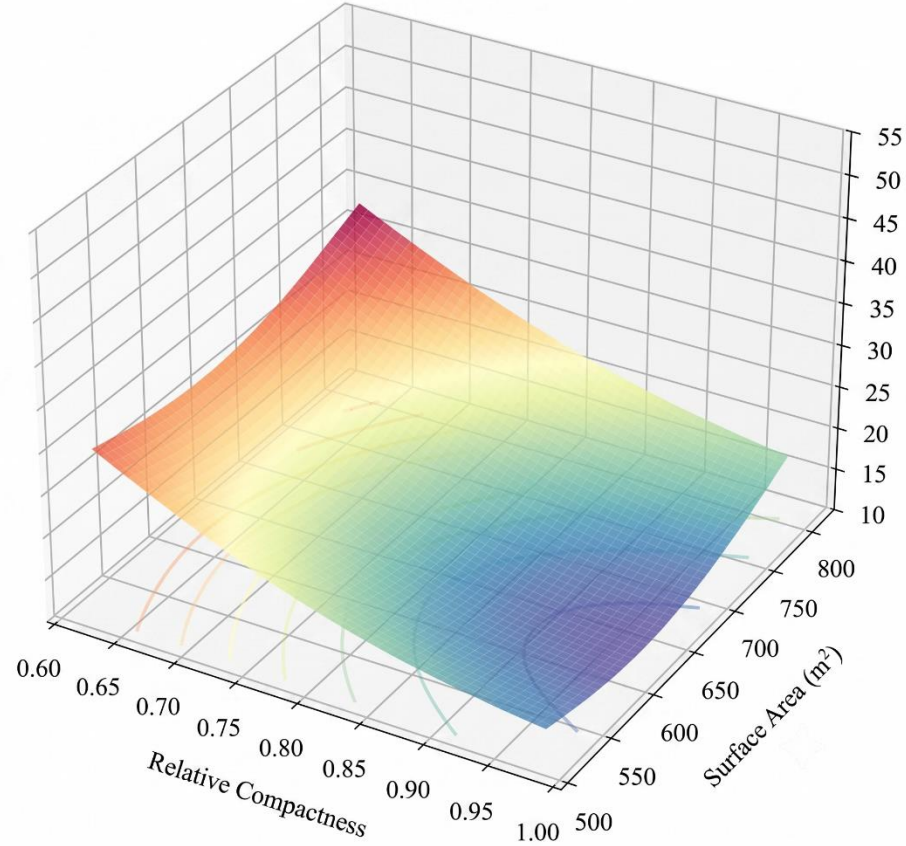


Fig. 12 Interaction effect of relative compactness and SA on Cooling Load

4.7. Interaction Analysis

Interaction analysis performed for the purpose of analyzing the combined impact of various input variables on the thermal loads. As illustrated in Figure. 12, the interaction of relative compactness and SA exhibits a better nonlinear influence on HL and CL. In particular, low compactness values of ≈ 0.60 and high surface area values of $\approx 900 \text{ m}^2$ lead to very high thermal loads of $\approx 45\text{-}50 \text{ kW}$ for CL, while increasing compactness to ≈ 1.00 leads to loads $\approx 15\text{-}20 \text{ kW}$ for CL, which is a reduction by 60-65%. In a similar way, for moderate SAs (approximately 700 m^2), an increase in compactness leads to a decrease in thermal load by around 30-40%, clearly indicating the significance of geometric efficiency. The influence of glazing area in combination with orientation also shown considerable influence over the cooling load, where increased glazing area in conjunction with specific orientation has led to an increase of roughly 10-15% of CL because of high solar heat gain. Furthermore, the combined influence of height along with SA has been found to positively correlate with thermal load, where tall buildings along with large SAs show an increase of around 20-25% in energy demand. Therefore, based on the findings, it concluded that the thermal load behavior depends upon the combined influence of geometric parameters and building envelope.

4.8. Comparison with Existing Models

The predictive performance of the proposed TabNet-ResMLP framework was compared with several existing ML and DL models for building thermal load prediction, as presented in Table 5. The GWO-CNN-LSTM framework achieved a 0.9266 of R^2 value for CL prediction using simulation-generated office building data; however, the model was validated under limited building configurations and climatic conditions. The XGBoost-based framework obtained an R^2 value of 0.92 for surface-level heat flux prediction using simulated thermal and environmental data from Danish residential and office buildings, although the approach focused mainly on winter heat-loss estimation rather than simultaneous HL and CL prediction.

The SSA-optimized Bi-LSTM model achieved an R^2 value of 0.965 using real-time operational HVAC data collected from industrial buildings across multiple seasons, but geometric and envelope-related parameters influencing whole-building thermal performance were not comprehensively incorporated. Similarly, the Random Forest (RF) framework achieved an R^2 value of 0.9482 using EnergyPlus-based office building simulation data, where prediction capability was constrained by the limited nonlinear interaction learning ability of conventional ensemble regression models. In contrast, the proposed TabNet-ResMLP framework achieved a 0.98 R^2 values for HL and 0.97 for CL using the Energy Efficiency dataset containing residential building geometric and envelope-related variables, including RC, SA, WA, RA, OA, GA, GD, and OH. Adaptive feature selection and contextual importance of the parameters were

achieved through the TabNet algorithm, whereas the regression consistency and learning nonlinear interactions between the dependent building features were provided by the ResMLP algorithm. Feature importance analysis, sensitivity analysis, and interaction analysis also indicated the effectiveness of the proposed architecture in identifying complex patterns of thermal behavior from structured building data. However, since the methods considered in the comparison study used distinct datasets, building categories, climatic settings, simulation environment, and sets of features, R^2 comparison not fully provide uniform conclusions regarding the comparative models' performance. Consequently, the results obtained through R^2 comparison are intended to serve as a general guide on the performance of approaches in the relevant literature.

Table 5. Performance comparison with existing methods

Author	Method / Model	R^2 Results
Zhang et al. [9]	GWO-CNN-LSTM	0.9266
Baset & Jradi [13]	XGBoost	0.92
Wei et al. [11]	SSA- Bi-LSTM	0.965
Chen et al. [19]	RF	0.9482
Proposed TabNet-ResMLP	TabNet-ResMLP	0.98 (HL), 0.97 (CL)

5. Conclusion

This study presented a hybrid TabNet- ResMLP framework for predicting HL and CL using the Energy Efficiency dataset. The proposed model effectively combined attentive feature selection and residual nonlinear regression to capture complex relationships between building parameters and thermal load behavior. Experimental outcomes demonstrated reliable predictive performance with 0.98 R^2 for HL and 0.97 R^2 for CL, along with low RMSE and MAE values, indicating accurate thermal load estimation. Feature importance, sensitivity, and interaction analyses further revealed that RC, SA, and OH significantly influenced energy demand, while optimized building geometry contributed to reduced thermal loads and improved energy efficiency. Compared with conventional machine learning and standalone DL approaches, the proposed framework provided improved interpretability and stable prediction capability, making it suitable for early-stage building energy assessment and sustainable design applications. The proposed TabNet-ResMLP framework can help architects and civil engineers to accurately predict the thermal load in the initial design process stage, taking into consideration geometric characteristics and envelope of the building.

The model can be used for energy-efficient building design, HVAC sizing, retrofit planning and sustainable building assessment. Moreover, its explainable feature analysis allows for making informed design decisions and for the creation of intelligent building energy management

systems. While the Energy Efficiency dataset is very popular for benchmarking, it is based on simulated residential buildings and takes only geometric and envelope parameters into account. The factors of occupant behavior, weather variation, HVAC operation, and material properties are not considered, and this might not be representative of buildings in the real world. To validate the proposed framework with real-world large-scale datasets and integrate real-time climatic data, future work will involve using more sophisticated transformer-based deep learning architectures and physics-

informed deep learning models to improve prediction accuracy and robustness.

Conflicts of Interest

“The author declares that there is no conflict of interest regarding the publication of this paper.”

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References

- [1] Fabrizio Ascione et al., “Design of the Building Envelope: A Novel Multi-Objective Approach for the Optimization of Energy Performance and Thermal Comfort,” *Sustainability*, vol. 7, no. 8, pp. 10809-10836, 2015. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [2] Yiqing Liu, Zhiwen Luo, and Sue Grimmond, “Impact of Building Envelope Design Parameters on Diurnal Building Anthropogenic Heat Emission,” *Building and Environment*, vol. 234, pp. 1-12, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [3] Ziyang Hao et al., “Simplified Model of Heat Load Prediction and Its Application in Estimation of Building Envelope Thermal Performance,” *Buildings*, vol. 13, no. 4, pp. 1-24, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [4] Meng Wang et al., “A Knowledge Graph-based Framework to Automate the Generation of Building Energy Models using Geometric Relation Checking and HVAC Topology Establishment,” *Energy and Buildings*, vol. 325, pp. 1-16, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [5] Rajendra Roka et al., “A Systematic Review of Sensitivity Analysis in Building Energy Modeling: Key Factors Influencing Building Thermal Energy Performance,” *Energies*, vol. 18, no. 9, pp. 1-27, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [6] Navid Shirzadi, Dominic Lau, and Meli Stylianou, “Surrogate Modeling for Building Design: Energy and Cost Prediction Compared to Simulation-Based Methods,” *Buildings*, vol. 15, no. 13, pp. 1-22, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [7] Youness El Mghouchi, and Mihaela Tinca Udristoiu, “Thermal Load Predictions in Low-Energy Buildings: A Hybrid AI-Based Approach Integrating Integral Feature Selection and Machine Learning Models,” *Applied Sciences*, vol. 15, no. 11, pp. 1-23, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [8] Osama Mohsen, “Machine Learning Framework for Predicting Thermal Performance of Building Envelopes in Early-Stage Architectural Design,” *Proceedings of International Structural Engineering and Construction*, pp. 1-6, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [9] Xuelong Zhang et al., “Building Cooling Load Prediction based on GWO-CNN-LSTM,” *Energies*, vol. 19, no. 2, pp. 1-19, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [10] Liliane Magnavaca de Paula, Amr Oloufa, and Omer Tatari, “BIM-based Machine Learning Framework for Early-Stage Building Energy Performance Prediction,” *Applied Sciences*, vol. 16, no. 1, pp. 1-22, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [11] Yingfeng Wei et al., “An Interpretable Building Air Conditioning Load Forecasting Framework using SSA-Optimized Bi-LSTM and SHAP Analysis,” *Frontiers in Environmental Science*, vol. 14, pp. 1-14, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [12] Nurlan Zhangabay et al., “Assessment and Numerical Modeling of the Thermophysical Efficiency of Newly Developed Adaptive Building Envelopes Under Variable Climatic Impacts,” *Buildings*, vol. 16, no. 2, pp. 1-28, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [13] Amjad Baset, and Muhyiddine Jradi, “Prioritizing Building Envelope Retrofits through Data-Driven Heat Flux Prediction,” *Journal of Building Engineering*, vol. 119, pp. 1-13, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [14] Nurlan Zhangabay et al., “Analysis of the Influence of the Geometry of a Ventilated Facade Subsystem on its Stress–Strain State and the Coefficient of Thermal Nonuniformity,” *Results in Engineering*, vol. 29, pp. 1-17, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [15] Alireza Karimi, David Moreno-Rangel, and Antonio García-Martínez, “AI-Driven Morphological Optimization for Resilient Retrofitting of Mediterranean Housing Stock under Compounded Urban Heat Island and HEATWAVE Effects,” *Building and Environment*, vol. 291, pp. 1-21, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [16] Liliane Magnavaca de Paula, Amr Oloufa, and Omer Tatari, “Integrating BIM and Machine Learning for Energy and Carbon Performance Prediction in Office Building Design,” *Eng*, vol. 7, no. 2, pp. 1-31, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [17] Simon Muhič et al., “Influence of Building Envelope Modeling Parameters on Energy Simulation Results,” *Sustainability*, vol. 17, no. 12, pp. 1-17, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [18] Dun Cao et al., “Research on the Distribution of the Energy-Saving Benefits of Building Geometric Parameters Under Different Climate Conditions,” *Buildings*, vol. 15, no. 17, pp. 1-19, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [19] Yongbao Chen et al., “Machine Learning Approach to Predict Building Thermal Load Considering Feature Variable Dimensions: An Office Building Case Study,” *Buildings*, vol. 13, no. 2, pp. 1-24, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]

- [20] Fayeze Abdel-Jaber, and Kim N. Dirks, “Thermal Load Prediction in Residential Buildings using Interpretable Classification,” *Buildings*, vol. 14, no. 7, pp. 1-14, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [21] Adam Slowik, and Dorin Moldovan, “Multi-Objective Plum Tree Algorithm and Machine Learning for Heating and Cooling Load Prediction,” *Energies*, vol. 17, no. 12, pp. 1-23, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [22] Shahid Mahmood et al., “Active Learning-based Machine Learning Approach for Enhancing Environmental Sustainability in Green Building Energy Consumption,” *Scientific Reports*, vol. 14, no. 1, pp. 1-18, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [23] Amal H. Alharbi et al., “Forecasting of Energy Efficiency in Buildings using Multilayer Perceptron Regressor with Waterwheel Plant Algorithm Hyperparameter,” *Frontiers in Energy Research*, vol. 12, pp. 1-16, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [24] Energy Efficiency Dataset, Kaggle. [Online]. Available: <https://www.kaggle.com/datasets/elikplim/energy-efficiency-dataset>
- [25] Kevin McDonnell et al., “Deep Learning in Insurance: Accuracy and Model Interpretability using TabNet,” *Expert Systems with Applications*, vol. 217, pp. 1-10, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [26] Xinya Zhou et al., “RMLP-Cap: An End-to-End Parasitic Capacitance Extraction Flow Based on ResMLP,” *Electronics*, vol. 15, no. 1, pp. 1-23, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]